

# Data Assimilation to Extract Soil Moisture Information From SMAP Observations

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# Outline



- Motivation
- Method
  - SMAP NN Retrievals
  - Data Assimilation Experiments
- Results
  - Impact on Soil Moisture Climatology
  - Evaluation vs. In Situ Measurements
  - Impact on Evaporation and Runoff
- Conclusions





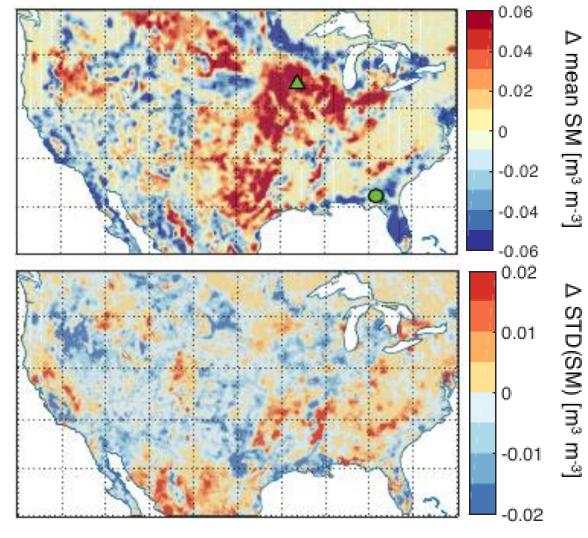
#### Objective:

Efficiently assimilate SMAP observations into the NASA Catchment model.

#### Issue:

Localized observation rescaling removes some independent information from very skillful SMAP retrievals.

Compare which rescaling method uses independent satellite information most efficiently.



**Fig 1.** Effect of localized bias correction (CDF-matching) on soil moisture retrieval.

# **SMAP Neural Network Retrievals**



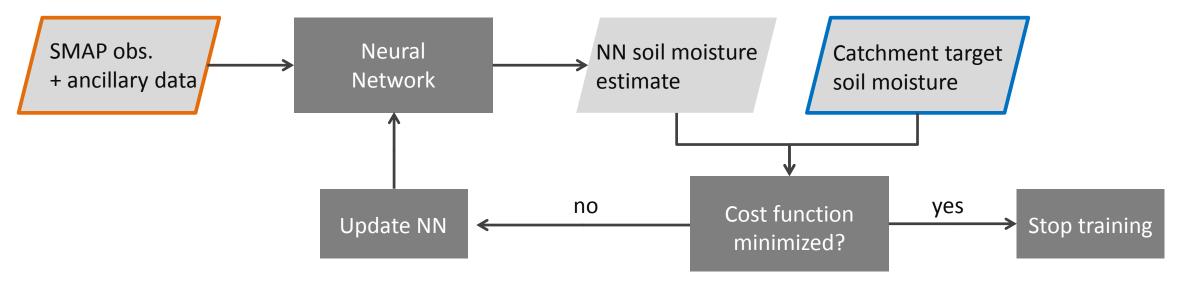


Fig 2. NN training procedure.

- Neural Networks (NN) <u>retrieve soil moisture in model climatology</u>
  (mean, variance, higher moments) (Kolassa et al. 2017, in review)
- Global dynamic range and bias from model (GEOS-5)
- Spatial and temporal patterns from observations (SMAP + ancillary data)

Can NN retrievals reduce the need for further bias correction prior to assimilation and thus avoid removing independent satellite information?



#### **SMAP Soil Moisture Assimilation**



#### **Experiments**

OL Model-only simulation (no assimilation)

DA-NN: Assimilate NN retrievals without further bias correction

• DA-NN-CDF: Assimilate NN retrievals with **local bias correction** 

DA-L2P-gCDF: Assimilate L2 passive retrievals (O'Neill et al., 2015) with global bias correction

DA-L4: Assimilate locally rescaled brightness temperatures in SMAP L4\_SM system

- April 2015 March 2017
- 9 km EASE v2 grid
- Contiguous United States
- 3-hourly analysis
- → Assess skill improvements of DA over OL at SMAP core validation sites

  (Jackson et al., 2016; Colliander et al., 2017)



# Impact on Soil Moisture Climatology



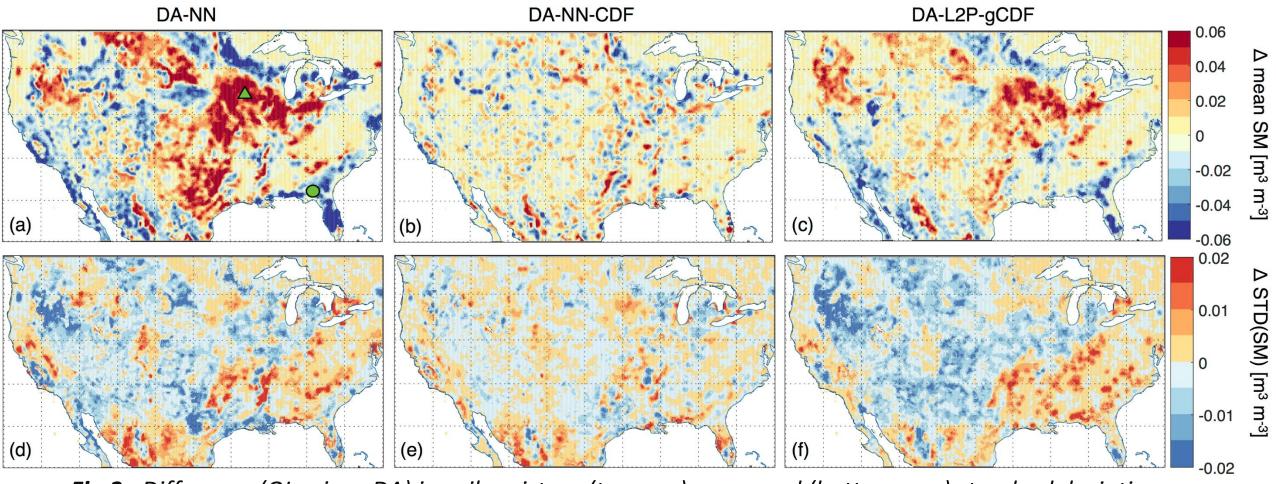


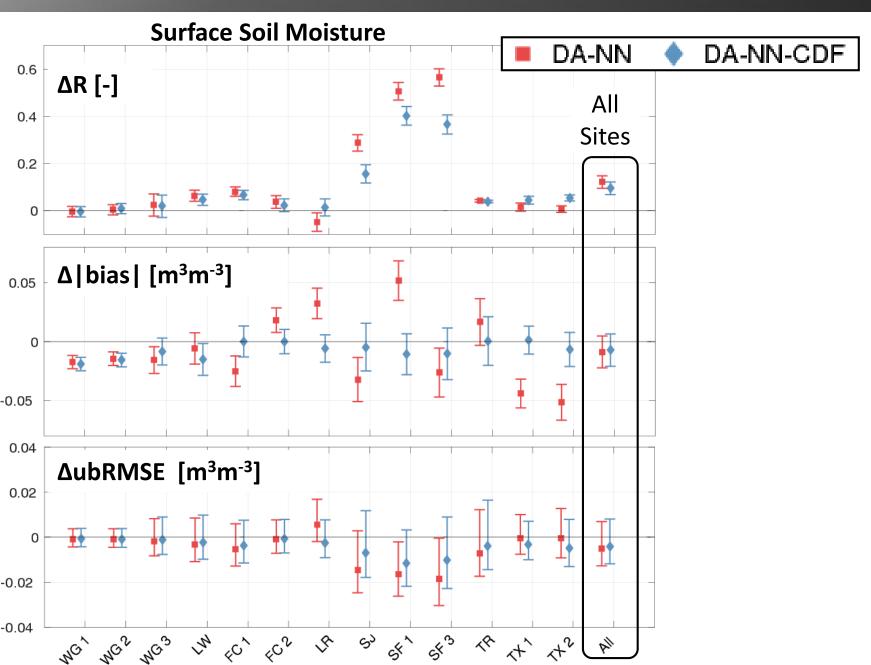
Fig 3. Difference (OL minus DA) in soil moisture (top row) mean and (bottom row) standard deviation.

Global rescaling experiments introduce more of the SMAP retrieval information.

- South Fork watershed
- Little River watershed

# Evaluation vs. In Situ Measurements: Global vs. Local Rescaling

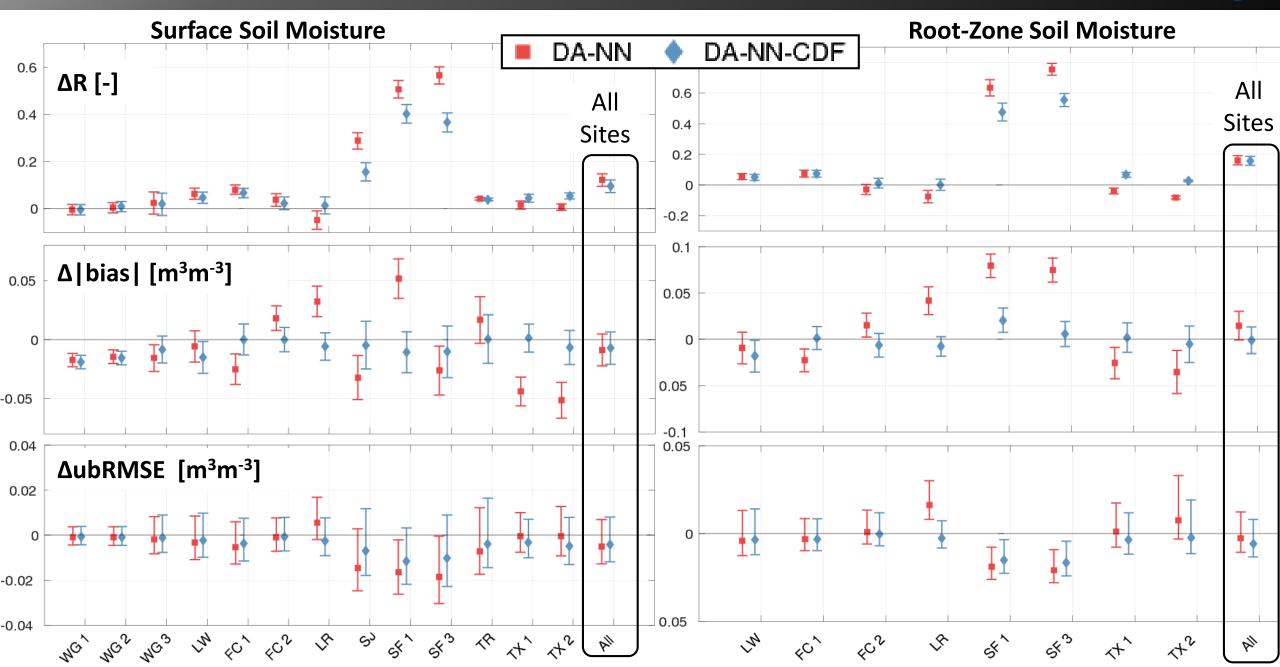






# Evaluation vs. In Situ Measurements: Global vs. Local Rescaling

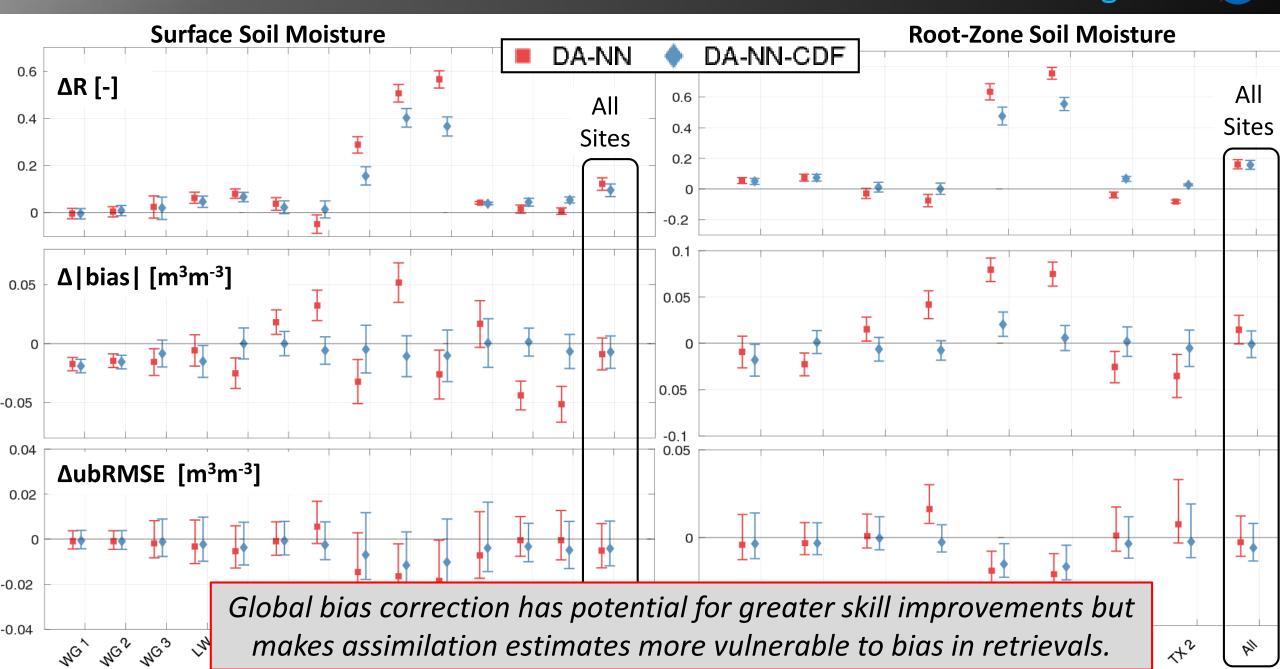




# GMAO

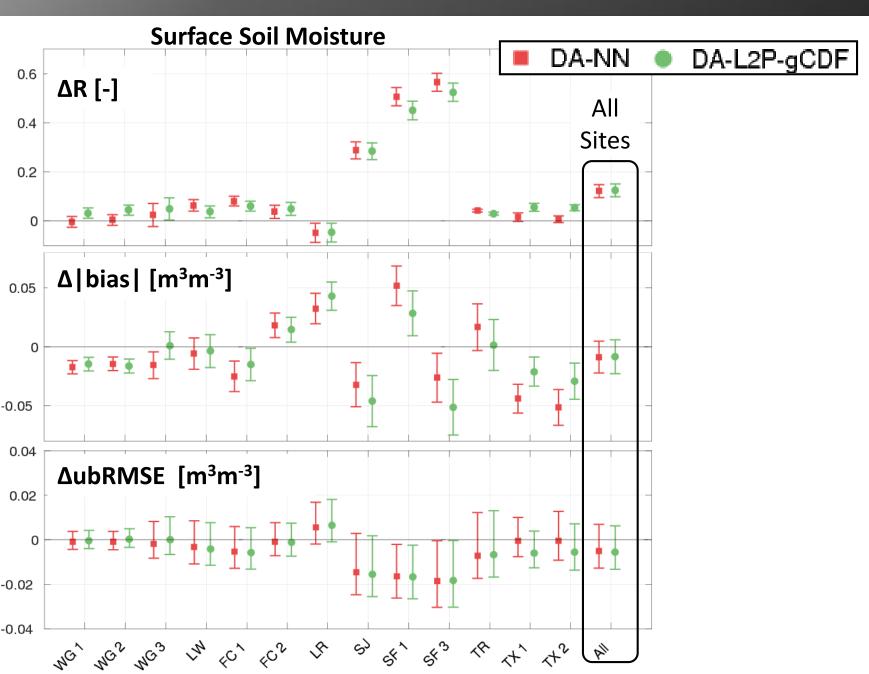
# Evaluation vs. In Situ Measurements: Global vs. Local Rescaling





# Evaluation vs. In Situ Measurements: NN vs. L2P Assimilation

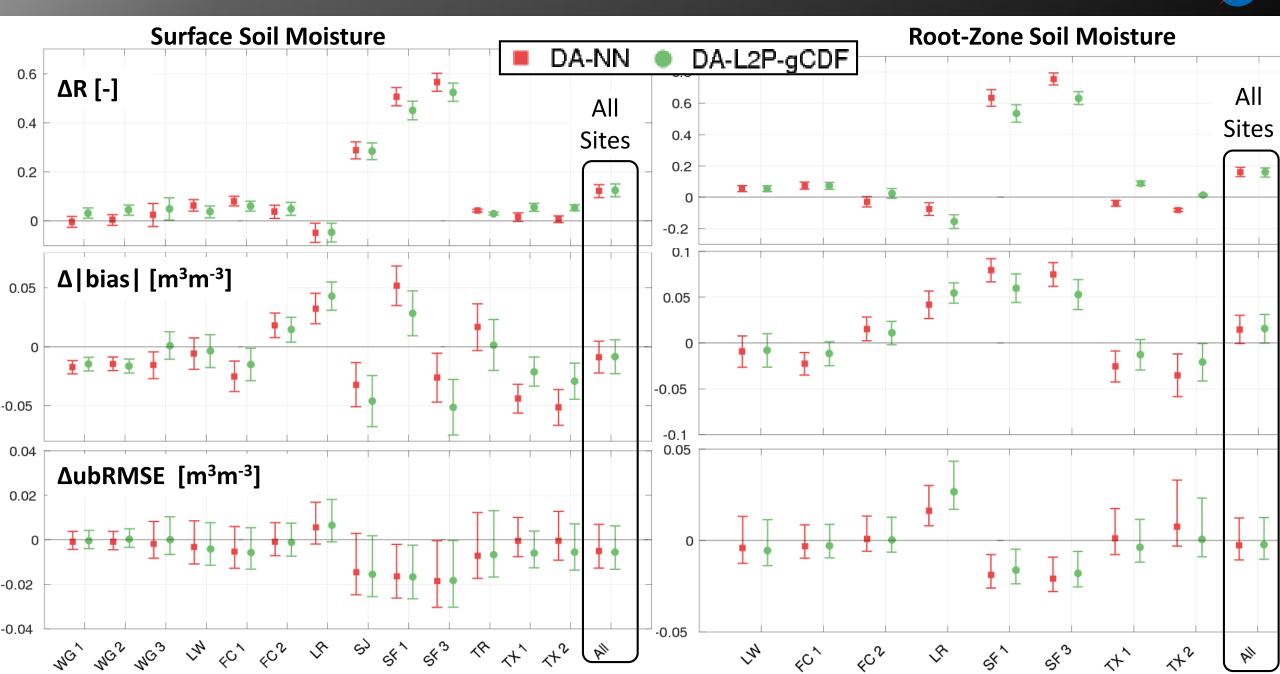






# Evaluation vs. In Situ Measurements: NN vs. L2P Assimilation

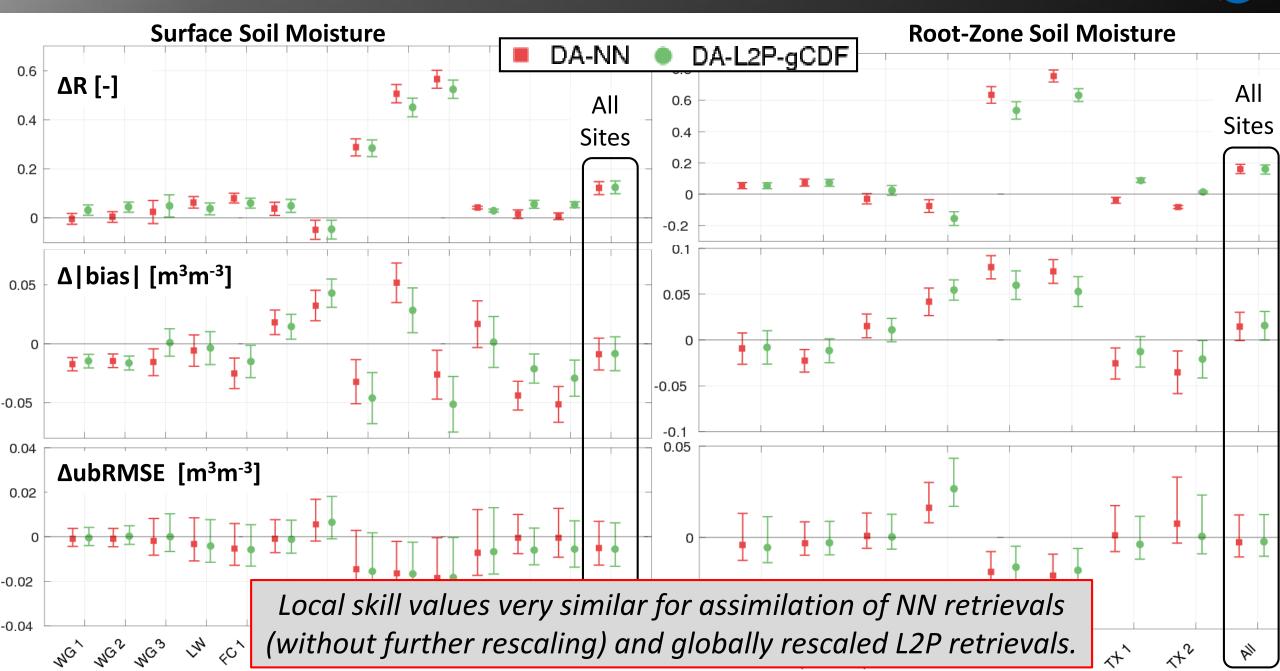






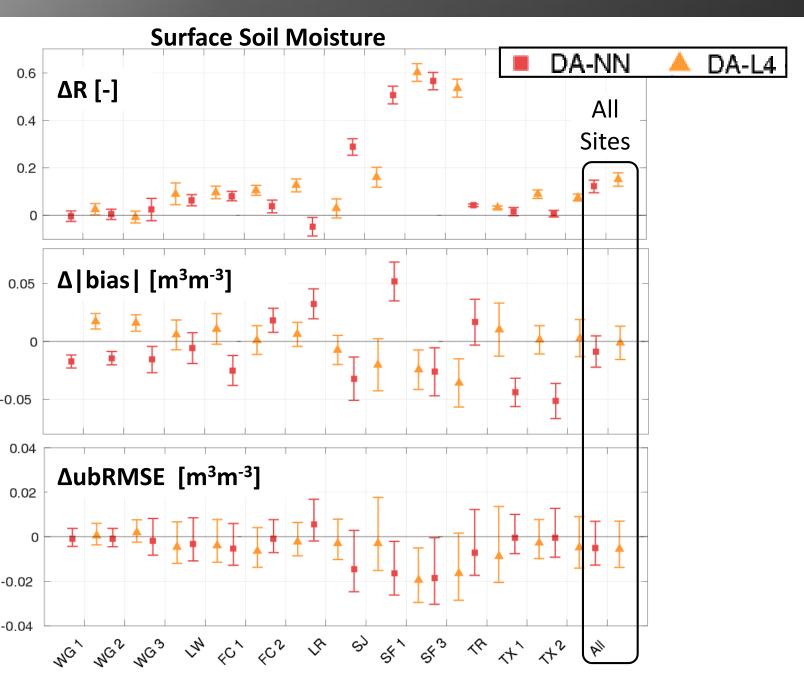
# Evaluation vs. In Situ Measurements: NN vs. L2P Assimilation





# Evaluation vs. In Situ Measurements: NN vs. Tb Assimilation

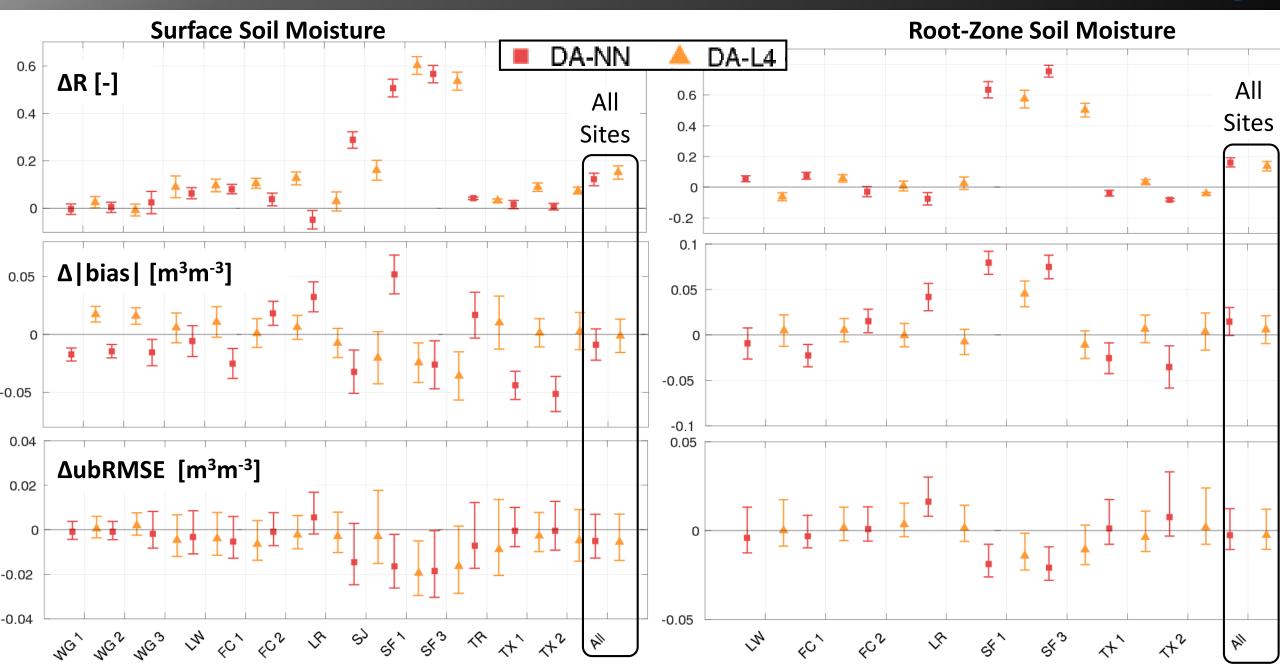






# Evaluation vs. In Situ Measurements: NN vs. Tb Assimilation

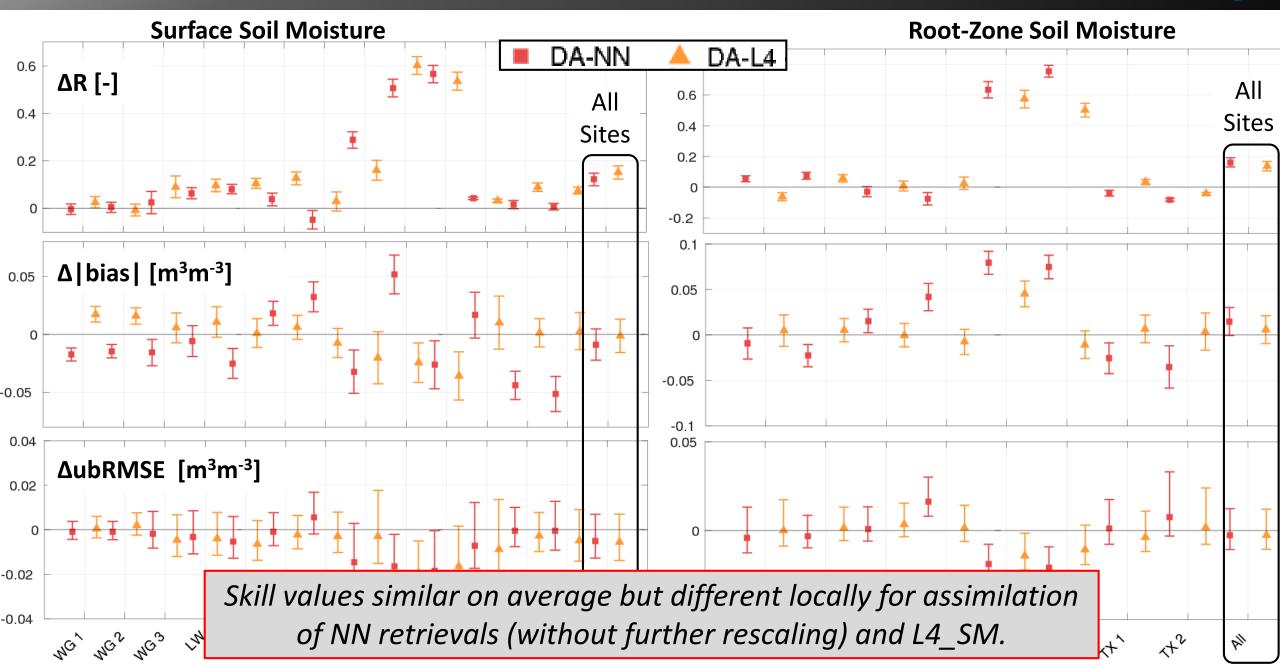






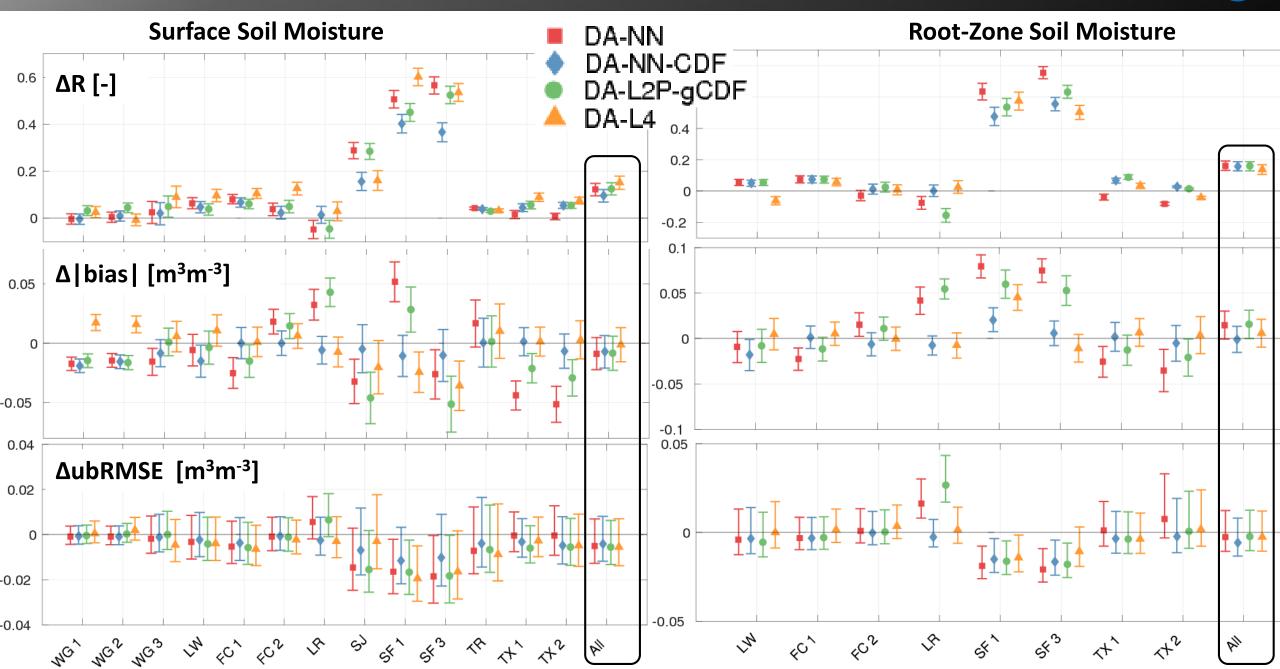
# Evaluation vs. In Situ Measurements: NN vs. Tb Assimilation





# **Evaluation vs. In Situ Measurements**





# Impact on Evapotranspiration and Runoff



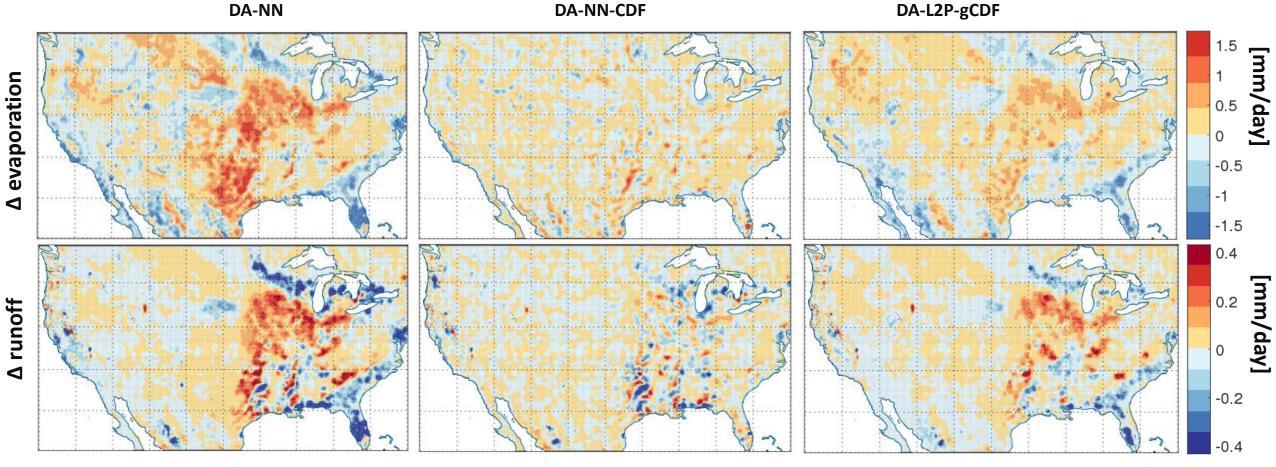


Fig 5. Difference (OL minus DA) in mean evaporation and runoff.

Evaporation and runoff changes reflect changes in soil moisture patterns where fluxes are sensitive to soil moisture.





- Global bias correction retains more independent satellite information.
  - Potential for greater improvements over model skill.
  - Assimilation skill more sensitive to retrieval bias.
  - Good QC and error characterization is crucial.
- Assimilation of NN and L2P retrievals (w/global rescaling) results in very similar local skill values.
- Soil moisture and Tb assimilation have similar average skill with local differences.
- Evaporation and runoff changes reflect changes in soil moisture patterns.

# References



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